

## Positioning of vehicle on undulating ground using GPS and dead reckoning

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**Abstract :** A method of positioning vehicle on undulating ground is proposed. This method uses GPS data and internal sensor data (fiber optic gyro, roll pitch sensor, and wheel encoders) and improve the positioning accuracy by compensating the error of each sensor data. A prototype of autonomous mower using this positioning method was produced and its positioning performance was evaluated. The experimental results show that the fusion system is more accurate than GPS only or internal sensor system. When the accuracy of GPS is 1m, the accuracy of the fusion system is 0.2m and this accuracy is enough to control vehicles. We expect that the positioning system for vehicle control can be realized using differential GPS whose accuracy is 1m, instead of using expensive kinematic GPS.

### 1. Introduction

There are two major methods of positioning vehicle. One of these is dead reckoning. In dead reckoning, the position of vehicle is calculated by accumulating the traveling distance in the direction the vehicle is traveling. The other category is absolute positioning[1], which detects landmarks and calculates the vehicle position using the relation between the vehicle and the landmark.

The problem in dead reckoning is error accumulation, caused by wheel slip and gyro drift. The error accumulation is greater in undulating ground than in flat ground. So landmark detecting seems to be necessary for vehicle positioning on undulating ground.

In absolute positioning, error accumulation doesn't occur, but setting landmarks and making their map is necessary. Recently GPS (Global Positioning System) [2] have become popular. In GPS, the landmarks (artificial satellites) and their map is prepared as infrastructure and position can be determined without considering the landmarks. There are various accuracy of GPS. The accuracy of GPS for car navigation is about 100m, that of differential GPS (D-GPS) is from 50 cm to 10 m, and that of kinematic GPS (K-GPS) is 2 or 3 cm. But K-GPS is too expensive and its sampling rate (1Hz) is not high enough for autonomous vehicle.

The purpose of this research is to develop an optimal sensor fusion system using D-GPS and the internal sensors (fiber optic gyro (FOG), roll pitch sensor and wheel encoders), to realize an accurate positioning system for vehicle control. Sensor fusion systems of GPS and

internal sensors have been developed for car navigation[3], but they are not accurate enough to control vehicle on undulating ground. Positioning vehicle on undulating ground accurately enough to control the vehicle that requires the following factors be considered.

(1) The effect of roll and pitch to yaw sensing.

The integral of the yaw rate on the vehicle coordinate system does not equal the yawing on the ground coordinate system.

(2) The delay and discontinuity of GPS data.

The GPS takes 0.2 second to calculate the position and outputs the position once a second. (The control interval is 0.05second.)

(3) The drift of fiber optic gyro.

(4) The traveling distance per encoder pulse is not constant.

(5) The GPS antenna is not fixed to the same position as the center of dead reckoning.

The first factor is particular to positioning on undulating ground, and factors (2)-(5) are common to positioning on undulating ground and positioning on flat ground. The purpose of this research is to develop positioning algorithm on undulating ground, which solves these 5 factors to make the best use of the GPS data and the internal sensor data.

In Section 2, the observation model of the GPS data and the internal sensor data, which considers these 5 factors, is described. Based on this observation model, the positioning method which make the best use of the GPS data and the internal sensor data is developed. Section 3 describes the production of an experimental autonomous mower using this positioning method. This mower is equipped with K-GPS. Various levels of noise were added to the K-GPS data to simulate various accuracies of GPS. Section 4 reports the positioning performance of the mower, and the relation between the accuracy of GPS and the accuracy of sensor fusion system is discussed.

### 2. Positioning method

Fig.1 illustrates the positioning system and Fig.2 shows the data flow in the positioning system. In this system, the wheel encoders measure the velocity, the fiber optic gyro measures the yaw rate on the vehicle coordinate system, the roll pitch sensor measures the rolling and pitching, and D-GPS measures the position of the vehicle. On undulating ground, the integral of the yaw rate on the

vehicle coordinate system does not equal the yawing on the ground coordinate system. The effect of rolling and pitching must be compensated to get the yawing on the ground coordinate system. The GPS uses the ellipsoidal coordinate system (latitude, longitude and height)[2] to output the position but the plane coordinate system (Cartesian coordinate system)[2] is more convenient for vehicle control. Sensor Fusion requires transforming the plane coordinate to the objective area coordinate (Cartesian coordinate system used for dead reckoning).

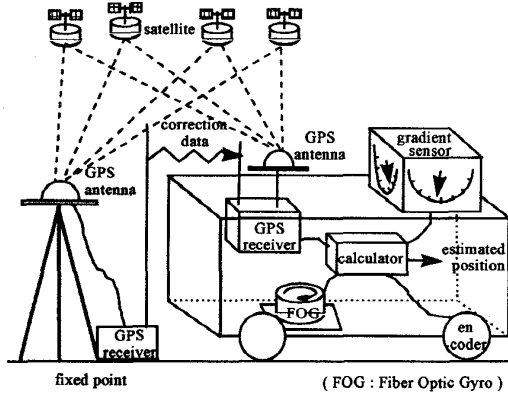


Fig.1 Positioning system

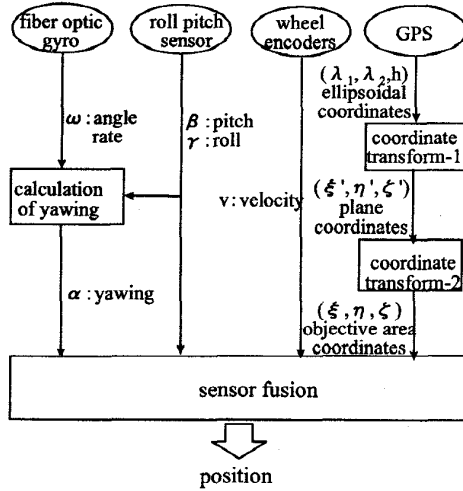


Fig.2 The flow of data processing

The positioning system calculates the vehicle position from the velocity, the yawing on the ground coordinate system, the rolling, the pitching and the position data from the GPS expressed in the objective area coordinate system. Because the position can be calculated from the internal sensor data, this system is redundant. An algorithm which make the best use of this redundancy to improve the positioning accuracy is developed in this section.

## 2.1 Calculation of yawing

In the positioning system of airplanes, three FOG fixed on the airplane measure the roll, pitch, yaw rate  $\omega_x, \omega_y, \omega_z$  on the vehicle coordinate system, and  $\omega_x, \omega_y, \omega_z$  are transformed into the rolling  $\gamma$ , the pitching  $\beta$ , the yawing  $\alpha$ , and the position is calculated from  $\gamma, \beta$  and  $\alpha$ . The transform is :

$$\begin{cases} \omega_x = \dot{\gamma} - \dot{\alpha} \sin \beta \\ \omega_y = \dot{\beta} \cos \gamma + \dot{\alpha} \cos \beta \sin \gamma \\ \omega_z = -\dot{\beta} \sin \gamma + \dot{\alpha} \cos \beta \cos \gamma \end{cases} \quad (1)$$

In the vehicle positioning system, rolling  $\gamma$  and pitching  $\beta$  are measured directly by the roll pitch sensor. From the third equation of (1),  $\alpha$  is calculated as:

$$\dot{\alpha} = (\omega_z + \dot{\beta} \sin \gamma) / \cos \beta \cos \gamma \quad (2)$$

Using  $\gamma, \beta, \alpha$  and velocity  $v$ , the position is calculated by the following expression.

$$\begin{cases} x_{i+1} = x_i + v_i \cos \beta_i \sin \alpha_i \Delta \\ y_{i+1} = y_i + v_i \cos \beta_i \cos \alpha_i \Delta \\ z_{i+1} = z_i + v_i \sin \beta_i \Delta \end{cases} \quad (3)$$

## 2.2 Observation model

In this subsection, an observation model of the internal sensors and the GPS is proposed. The observation model consists of the internal sensor model and the GPS model.

To develop the internal sensor model, the errors of sensor data are introduced :

- $\rho$  : the error of the velocity
- $\theta$  : the error of the yawing
- $\phi$  : the error of the pitching
- $\psi$  : the error of the rolling

The true value of the velocity, yawing, pitching and rolling can be expressed as  $(v + \rho), (\alpha + \theta), (\beta + \phi)$  and  $(\gamma + \psi)$ . The position of the vehicle (the position of the midpoint of the two non-steering wheels) can be calculated by the following expression.

$$\begin{cases} x_{i+1} = x_i + (v_i + \rho_i) \cos(\beta_i + \phi_i) \sin(\alpha_i + \theta_i) \Delta \\ y_{i+1} = y_i + (v_i + \rho_i) \cos(\beta_i + \phi_i) \cos(\alpha_i + \theta_i) \Delta \\ z_{i+1} = z_i + (v_i + \rho_i) \sin(\beta_i + \phi_i) \Delta \end{cases} \quad (4)$$

We modeled the error process as random walk models.

$$\begin{cases} \rho_{i+1} = \rho_i + u_{1i} \\ \theta_{i+1} = \theta_i + u_{2i} \\ \phi_{i+1} = \phi_i + u_{3i} \\ \psi_{i+1} = \psi_i + u_{4i} \end{cases} \quad (5)$$

where  $u_1, u_2, u_3$  and  $u_4$  are white noise.

To develop the GPS model, the vector from the midpoint of the non-steering wheel to the antenna is defined:

$$\mathbf{a} = (0 \ -S \ H)(n_x \ n_y \ n_z)^T \quad (6)$$

where  $n_x, n_y, n_z$  is the unit vector of the vehicle coordinate system.

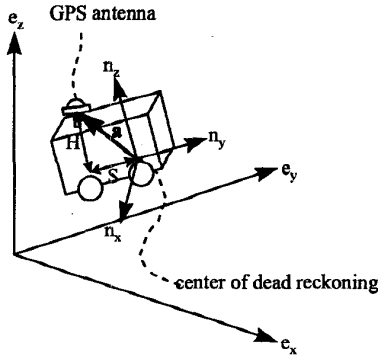


Fig.3 The position of GPS antenna and the center of dead reckoning

The transform of ground coordinate system ( $e_x, e_y, e_z$ ) to vehicle coordinate system ( $n_x, n_y, n_z$ ) is expressed as:

$$\begin{pmatrix} n_x \\ n_y \\ n_z \end{pmatrix} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & \cos(\gamma+\psi) & \sin(\gamma+\psi) \\ 0 & -\sin(\gamma+\psi) & \cos(\gamma+\psi) \end{pmatrix} \begin{pmatrix} e_x \\ e_y \\ e_z \end{pmatrix} \quad (7)$$

$$\begin{pmatrix} \cos(\beta+\phi) & 0 & -\sin(\beta+\phi) \\ 0 & 1 & 0 \\ \sin(\beta+\phi) & 0 & \cos(\beta+\phi) \end{pmatrix} \begin{pmatrix} e_x \\ e_y \\ e_z \end{pmatrix}$$

$$\begin{pmatrix} \cos(\alpha+\theta) & \sin(\alpha+\theta) & 0 \\ -\sin(\alpha+\theta) & \cos(\alpha+\theta) & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} e_x \\ e_y \\ e_z \end{pmatrix}$$

From (6) and (7), the vector  $\mathbf{a}$  is represented as:

$$\mathbf{a} = \begin{pmatrix} 0 & -S & H \end{pmatrix} \begin{pmatrix} n_x & n_y & n_z \end{pmatrix}^T \quad (8)$$

$$= \begin{pmatrix} q\sin(\alpha+\theta)+H\sin(\gamma+\psi)\cos(\alpha+\theta) \\ q\cos(\alpha+\theta)-H\sin(\gamma+\psi)\sin(\alpha+\theta) \\ -S\sin(\beta+\phi)+H\cos(\gamma+\psi)\cos(\beta+\phi) \end{pmatrix}^T \begin{pmatrix} e_x \\ e_y \\ e_z \end{pmatrix}$$

$$\equiv \begin{pmatrix} k & l & m \end{pmatrix} \begin{pmatrix} e_x \\ e_y \\ e_z \end{pmatrix}$$

where

$$q = -S\cos(\beta+\phi) - H\cos(\gamma+\psi)\sin(\beta+\phi) \quad (9)$$

Considering this vector  $\mathbf{a}$  and the delay of GPS data  $D$ , the relation between the vehicle position ( $x, y, z$ ) and the GPS data ( $\xi, \eta, \zeta$ ) can be written as:

$$\begin{cases} \xi_{c(i)} = x_{c(i)-D} + k_{c(i)-D} + \delta_{c(i)-D} \\ \eta_{c(i)} = y_{c(i)-D} + l_{c(i)-D} + \varepsilon_{c(i)-D} \\ \zeta_{c(i)} = z_{c(i)-D} + m_{c(i)-D} + \kappa_{c(i)-D} \end{cases} \quad (10)$$

where  $c(i)$  is the time when the  $i$ th data is received and ( $\delta, \varepsilon, \kappa$ ) is white noise.

Because  $\rho, \theta, \phi, \psi \ll 1$ , the observation model (4), (5) and (10) can be rewritten as

$$\begin{cases} \text{Dead Reckoning: } \mathbf{x}_{i+1} = \mathbf{A}_i \mathbf{x}_i + \mathbf{b}_i + \mathbf{u}_i \\ \text{GPS: } \mathbf{y}_{c(i)} = \mathbf{C}_i \mathbf{x}_{c(i)-D} + \mathbf{d}_i + \mathbf{v}_i \end{cases} \quad (11)$$

where

$$\mathbf{x}_i = (x_i, y_i, z_i, \rho_i, \theta_i, \phi_i, \psi_i)^T \quad (12)$$

$$\mathbf{b}_i = v_i (\cos\beta_i \sin\alpha_i, \cos\beta_i \cos\alpha_i, \sin\beta_i, 0, 0, 0, 0)^T \quad (13)$$

$$\mathbf{u}_i = (0, 0, 0, u_{1i}, u_{2i}, u_{3i}, u_{4i})^T \quad (14)$$

$$\mathbf{A}_i = \begin{pmatrix} E_3 & \begin{matrix} \cos\beta_i \sin\alpha_i & v_i \cos\beta_i \cos\alpha_i & -v_i \sin\beta_i \sin\alpha_i & 0 \\ \cos\beta_i \cos\alpha_i & -v_i \cos\beta_i \sin\alpha_i & -v_i \sin\beta_i \cos\alpha_i & 0 \\ \sin\beta_i & 0 & v_i \cos\beta_i & 0 \end{matrix} \\ O & E_4 \end{pmatrix} \quad (15)$$

$$\mathbf{d}_i = \begin{pmatrix} -(S\cos\beta_i + H\cos\gamma_i \sin\beta_i) \sin\alpha_i + H\sin\gamma_i \cos\alpha_i \\ -(S\cos\beta_i + H\cos\gamma_i \sin\beta_i) \cos\alpha_i - H\sin\gamma_i \sin\alpha_i \\ -S\sin\beta_i + H\cos\gamma_i \cos\beta_i \end{pmatrix} = \begin{pmatrix} k_i' \\ l_i' \\ m_i' \end{pmatrix} \quad (16)$$

$$\mathbf{C}_i = \begin{pmatrix} E_3 & \begin{matrix} 0 & l_i' & (S\sin\beta_i - H\cos\gamma_i \cos\beta_i) \sin\alpha_i \\ 0 & -k_i' & (S\sin\beta_i - H\cos\gamma_i \cos\beta_i) \cos\alpha_i \\ 0 & 0 & -(S\cos\beta_i + H\cos\gamma_i \sin\beta_i) \end{matrix} \end{pmatrix} \quad (17)$$

$$\begin{pmatrix} H(\sin\gamma_i \sin\beta_i \sin\alpha_i + \cos\gamma_i \cos\alpha_i) \\ H(\sin\gamma_i \sin\beta_i \cos\alpha_i - \cos\gamma_i \sin\alpha_i) \\ -H\sin\gamma_i \cos\beta_i \end{pmatrix}$$

$$\begin{pmatrix} k' \\ l' \\ m' \end{pmatrix} = \begin{pmatrix} (-S\cos\beta - H\cos\gamma \sin\beta) \sin\alpha + H\sin\gamma \cos\alpha \\ (-S\cos\beta - H\cos\gamma \sin\beta) \cos\alpha - H\sin\gamma \sin\alpha \\ -S\sin\beta + H\cos\gamma \cos\beta \end{pmatrix} \quad (18)$$

$$\mathbf{v}_i = (\delta_{c(i)-D}, \varepsilon_{c(i)-D}, \kappa_{c(i)-D})^T \quad (19)$$

Equation (11) shows the linear model of observation process considering the factors (1)(2)(3)(4)(5) mentioned in Section 1.

### 2.3 Method of position calculation

In this section, the position-error vector  $\mathbf{x}_{e(i)}$  is calculated from the internal sensor data ( $v, a, \beta, \gamma$ ) and the GPS data  $\mathbf{y}_{e(i)}$ .

A transformation of the observation model becomes Kalman filter model. This transformation is proposed and the position-error vector is calculated based on the Kalman filter method.

From (11),

$$\mathbf{x}_{c(i)-D} = (\mathbf{A}_{c(i)-D-1} \cdots \mathbf{A}_{c(i-1)-D}) \mathbf{x}_{c(i-1)-D} + \sum_{n=c(i-1)-D}^{c(i)-D-1} (\mathbf{A}_{c(i)-D-1} \cdots \mathbf{A}_{n+1}) (\mathbf{b}_n + \mathbf{u}_n) \quad (20)$$

The observation model (11) can be rewritten as

$$\begin{cases} \mathbf{z}_i = \mathbf{F}_i \mathbf{z}_{i-1} + \mathbf{g}_i + \mathbf{h}_i \\ \mathbf{s}_i = \mathbf{C}_i \mathbf{z}_i + \mathbf{d}_i + \mathbf{v}_i \end{cases} \quad (21)$$

where

$$\begin{cases} \mathbf{F}_i = \mathbf{A}_{c(i)-D-1} \cdots \mathbf{A}_{c(i-1)-D} \\ \mathbf{g}_i = \sum_{n=c(i-1)-D}^{c(i)-D-1} (\mathbf{A}_{c(i)-D-1} \cdots \mathbf{A}_{n+1}) \mathbf{b}_n \\ \mathbf{h}_i = \sum_{n=c(i-1)-D}^{c(i)-D-1} (\mathbf{A}_{c(i)-D-1} \cdots \mathbf{A}_{n+1}) \mathbf{u}_n \end{cases} \quad (22)$$

$$\begin{cases} \mathbf{z}_i = \mathbf{x}_{c(i)-D} \\ \mathbf{s}_i = \mathbf{y}_{c(i)} \end{cases} \quad (23)$$

The vector  $\mathbf{z}$  is estimated by applying the Kalman filter method to the observation model (21)

The estimation process is as follows:

(1)  $\text{Var}[\mathbf{z}_i | y_0, \dots, y_{i-1}, \text{internal sensor data}]$  is calculated.

$$\mathbf{M}_i = \mathbf{F}_i \mathbf{P}_{i-1} \mathbf{F}_i^T + \mathbf{U}_i \quad (24)$$

(2)  $\mathbf{z}_i$  is calculated from  $y_0, \dots, y_{i-1}$  and internal sensor data

$$\hat{\mathbf{z}}_i = \mathbf{F}_i \hat{\mathbf{z}}_{i-1} + \mathbf{g}_i \quad (25)$$

(3)  $\text{Var}[\mathbf{z}_i | y_0, \dots, y_i, \text{internal sensor data}]$  is calculated.

$$\mathbf{P}_i = \mathbf{M}_i - \mathbf{M}_i \mathbf{C}_i^T \{ \mathbf{V}_i + \mathbf{C}_i \mathbf{M}_i \mathbf{C}_i^T \}^{-1} \mathbf{C}_i \mathbf{M}_i \quad (26)$$

(4)  $\mathbf{z}_i$  is calculated from  $y_0, \dots, y_i$  and internal sensor data

$$\hat{\mathbf{z}}_i = \hat{\mathbf{z}}_i + \mathbf{P}_i \mathbf{C}_i^T \mathbf{V}_i^{-1} (\mathbf{s}_i - \mathbf{C}_i \hat{\mathbf{z}}_i - \mathbf{d}_i) \quad (27)$$

where

$$\mathbf{U}_i = E[\mathbf{h}_i - \bar{\mathbf{h}}_i][\mathbf{h}_i - \bar{\mathbf{h}}_i]^T \quad (28)$$

$$\mathbf{V}_i = E[\mathbf{v}_i - \bar{\mathbf{v}}_i][\mathbf{v}_i - \bar{\mathbf{v}}_i]^T$$

Using  $\mathbf{z}_i = \mathbf{x}_{c(i)-D}$ , the present position is calculated as: when GPS data is received,

$$\hat{\mathbf{x}}_{c(i)} = (\mathbf{A}_{c(i)} \dots \mathbf{A}_{c(i)-D+1}) \hat{\mathbf{x}}_i + \sum_{n=c(i)-D}^{c(i)-1} (\mathbf{A}_{c(i)-1} \dots \mathbf{A}_{n+1}) \mathbf{b}_n \quad (29)$$

when GPS data is not received,

$$\hat{\mathbf{x}}_{i+1} = \mathbf{A}_i \hat{\mathbf{x}}_i + \mathbf{b}_i \quad (30)$$

### 3. Experimental production of an autonomous mower

#### 3.1 Control system

To evaluate the positioning algorithm developed in Section 2, we produced an experimental autonomous mower which traces a given path. Fig.4 shows the experimental autonomous mower. This is converted from a manual mower and its accelerator and steering can be controlled by the controller. It is equipped with a K-GPS, a fiber optic gyro, a roll pitch sensor and two wheel encoders. The accuracy of K-GPS is 2 or 3 cm. The fiber optic gyro is closed loop type, whose drift rate is 0.5deg/h. The encoder generates 100 pulses per wheel revolution. The base of the controller is DX4-100MHz PC.

Fig.5 shows the block diagram of the control system. The vehicle position is estimated using the yaw rate measured by the fiber optic gyro, the rolling and pitching measured by the roll pitch sensor, the velocity measured by the wheel encoders and the position which is sum of the GPS data and various levels of white noise. Based on the difference between the reference path and this estimated position, the control signal to the accelerator and the steering is calculated. The interval of positioning and control is 50msec.



Fig.4 Autonomous mower

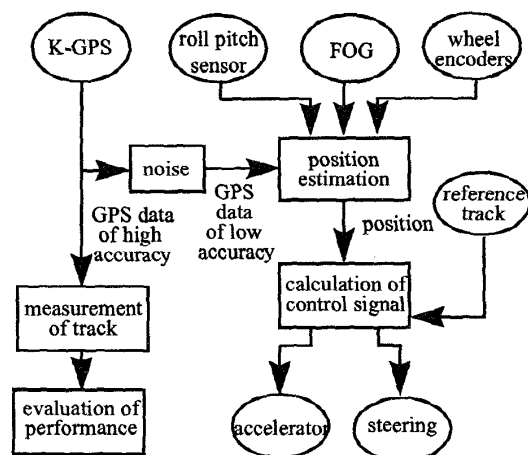


Fig.5 The block diagram of the control system

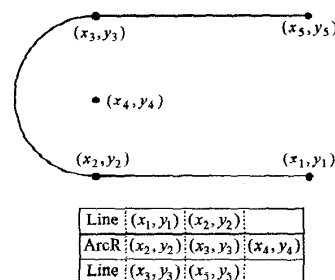


Fig.6 Reference path

#### 3.2 Reference path

The reference path consists of line segments and arc segments. Fig.6 shows the data format of the reference path. A row of the table in Fig.6 corresponds to a segment of the reference path. The first column is the type of the segment, the second is the starting point, the third is the ending point, and if the segment is arc, the fourth is the

center of the arc. The segment to be followed by the vehicle is determined on the basis of the measured position of the vehicle. The next segment is followed when the terminating condition for the current segment is satisfied.

### 3.3 Steering control

The control algorithm of the steering consists of two steps. The first step is calculation of the reference direction based on the displacement of the measured position from the reference path. The second step is calculation of control signal for steering which make the vehicle direction follow the reference direction.

The reference direction is calculated as :

$$\alpha_r = \arg(\vec{t} + k\vec{n}) \quad (31)$$

where  $\vec{t}$  is the tangent vector of the reference path and  $\vec{n}$  is the perpendicular vector from the measured position to the reference path.  $k$  is the parameter for the smoothness of the vehicle trajectory. When  $k$  is large, the vehicle trajectory converges to the reference path rapidly, and when  $k$  is small, the vehicle converges to the reference path smoothly. Parameter  $k$  is fixed in advance on basis of experiments.

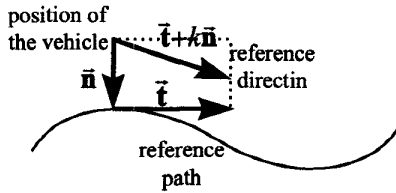


Fig.7 Calculation of the reference direction

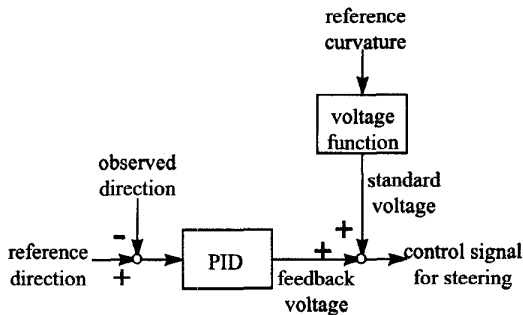


Fig.8 Calculation of the control signal for steering

The control signal for steering is given as the sum of the standard voltage, which is the function of the curvature of the reference path, and the feedback voltage, which is calculated by PID controller according to the difference between the measured direction and the reference direction.

### 3.4 Accelerator Control

The pattern of the control signal for the accelerator is given in advance. The accelerator is controlled by the control signal which is determined by the measured position.

## 4. Experiments

The mower traveled on undulating ground and its positioning performance was evaluated. Because accurate GPS is expensive, the relation between the accuracy of the GPS and the accuracy of the sensor fusion system is interesting. The controller added various levels of white noise to the K-GPS data and at each level of noise the positioning performance of the sensor fusion system was recorded. The control performance was evaluated using the difference between the position estimated by the sensor fusion system and the position of the K-GPS data without noise.

### 4.1 Experimental conditions

The undulating ground used for the experiments is shown in Fig.9. The reference path was input to the mower in advance. It consisted of parallel lines and arcs connecting the lines as shown in Fig.10. The mower traveled the lines with a velocity of about 5Km/h and decreased its velocity in the arcs. The trajectories of the mower measured by the sensor fusion system and the K-GPS were recorded each second for 12minutes. The difference between the trajectory measured by the sensor fusion system and the trajectory measured by the K-GPS system was used for the evaluation.

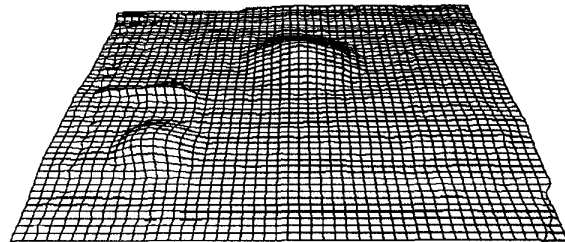


Fig.9 The undulating ground for the experiment

The standard deviations of the white noise added to the K-GPS data were 0.01m, 0.5m, 1m and 5m. In each standard deviation of the K-GPS data noise, the performance of the sensor fusion system was compared with the performance of the dead reckoning system. The standard deviation of the gyro error  $u_2, u_3, u_4$  was set to  $0.31 \times 10^{-6}$  [deg/s] and the standard deviation of the velocity error  $u_1$  was set to  $0.31 \times 10^{-6}$  [m/s].

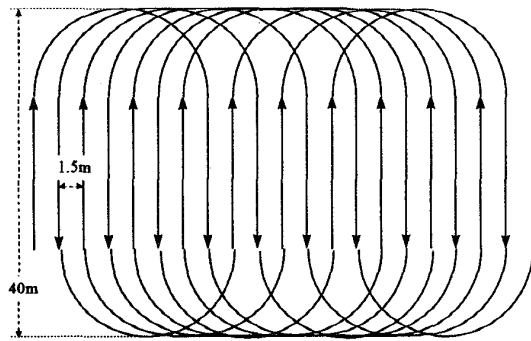


Fig.10 The reference path

#### 4.2 Experimental results

Fig.11 shows the sequence of positioning error of the sensor fusion system and the dead reckoning system, where the accuracy of the GPS is 0.25m. This figure shows that the amplitude of the positioning error of the dead reckoning system grows with time. However, the range of the positioning error of the GPS system is limited. The sequences of the positioning error of other GPS accuracies are omitted and show the same tendency as Fig.11.

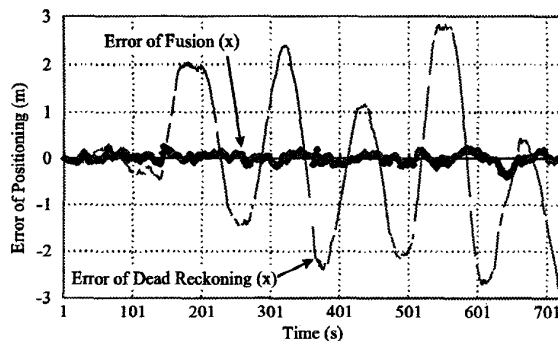


Fig.11 The time series of the error of positioning

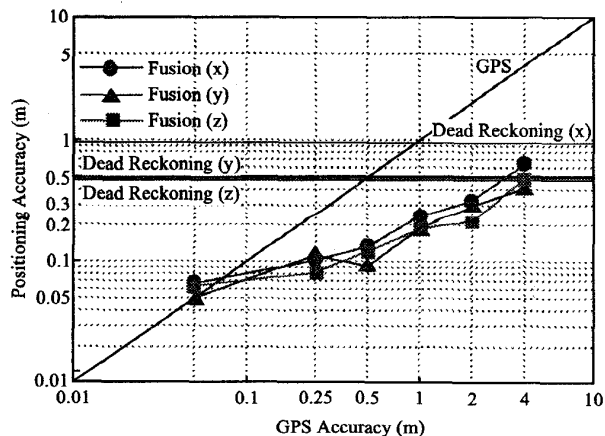


Fig.12 The relation between the GPS accuracy and the positioning accuracy of the fusion system

Fig.10 shows the relation between the accuracy (the standard deviation of positioning error) of the GPS and the accuracy of the sensor fusion system. The accuracy of GPS alone and the accuracy of dead reckoning are also shown. This figure shows that the accuracy of the sensor fusion system is not proportional to the GPS accuracy and converges to the accuracy of dead reckoning. When the accuracy of the GPS is 1m, the accuracy of the sensor fusion system is 0.2m.

The accuracy of dead reckoning is the standard deviation of positioning error which was recorded for 12 minutes. If positioning error is recorded for longer term, the accuracy of dead reckoning will be worse. The line showing the accuracy level of dead reckoning in Fig.10 will shift upward. Thus the effect of sensor fusion will be more remarkable if the positioning is performed for a longer term.

These experimental results shows that the sensor fusion system makes possible an accurate positioning system, whose accuracy continues for a long term. If the accuracy of GPS is 1m, the accuracy of the sensor fusion system is 0.2m, which is sufficient for vehicle control.

#### 5. Conclusion

A method of vehicle positioning using a fiber optic gyro, roll pitch sensor, wheel encoders and GPS is proposed. This method compensates the error of the internal sensors and the GPS to improve the positioning accuracy. An experimental autonomous mower was produced to evaluate the performance of the positioning system. The experimental results show that the sensor fusion improves the positioning accuracy. When the accuracy of the GPS is 1m, the accuracy of the sensor fusion system is 0.2m. We expect that the positioning system for vehicle control can be realized using D-GPS, whose accuracy is 1m.

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